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Multi-objective optimization of building envelope for energy consumption and daylight

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Abstract

The objective of this article is to provide a methodology for optimizing the envelope of a building with respect to the triple objective of heating load, cooling load and daylight. The variables to optimize are the window to wall area ratio (WWR) and the window type characterized by its visual and thermal characteristics (visual and solar transmittance, and U-value). Energy load is computed using building performance simulation software (TRNSYS). A criterion of daylight is defined as the integrated time when the illuminance is below a threshold and artificial light is required. This criterion was calculated using the software Daysim. The variables have antagonistic effects on the objectives: WWR and window type may have opposite effects by increasing solar gain and daylight duration during winter, which would be beneficial, but could lead to overheating during summer. Therefore, an easy-to-set up methodology is proposed to find the optimal solutions of such a problem. A multi-objective optimization was performed in order to find the optimal variables leading to the minimization of the energy load and the maximization of the indoor daylight duration. The method was applied to a dormitory retrofitting. Optimal solutions are the best compromise among antagonistic objectives and would offer guidance to designers in making construction decisions.

Keywords

Building envelope, Daylight, Energy performance, Illuminance, Multi-objective optimization

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Introduction

Optimization studies have been conducted in building science in recent years after long being computationally intractable. In the field of building science, the systems of interest are extremely complex, with a high number of variables, non-linear equations, and simulation durations often as large as one year. As a consequence, optimizing such systems is a difficult task. Yet, novel optimization methods have lately been adapted to building science problems, enabling a wide range of new studies.

Studies addressing optimization in building science centre on the optimization of multi-scale systems. These systems are ranging from the construction element,[1] through the buildings' envelope and Heating, Ventilation, and Air Conditioning (HVAC) systems[2–5] to building design.[6,7] All these studies have specific objective-functions adapted to the problem. Sambou et al.[1] proposed to build a construction element made of multilayered walls or partitioned cavities that would be simultaneously insulated (by maximizing thermal resistance) and with high inertia (by maximizing thermal capacity determined with the quadrupole theory). The variables are the thermal properties of the materials and the geometry of the element. Some studies[2–4] address the building envelope, seeking optimal variables that minimize energy consumption while maintaining thermal comfort; the variables being, for example, the thermophysical properties of the envelope,

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the shading devices, or the HVAC systems. Investigations of optimal building shapes have been performed; in Wang et al.[6] look for optimal shapes that minimize life-cycle cost and environmental impact; in Tuhus-Dubrow and Krarti[7] do the same in order to minimize energy use.

In all these studies, when the energy consumption of the building is involved as an objective-function, it is solved with transient simulation software such as TRNSYS, Energy+, or simplified models.[8] Yet, only by minimizing the energy consumption would lead to optimal solutions that are unacceptable for thermal comfort. Maintaining thermal comfort can be done by either adding constraints to eliminate unacceptable solutions, or by adding other objective-functions. As a summary, the objective-functions used to date in all these studies are energy load, thermal comfort, and life-cycle cost.

Daylight can have a large influence on environmental condition to improve visual comfort.[9] Hwang and Kim[10] have shown that daylight could improve the occupants' psychological health and productivity. Daylight is therefore a relevant parameter to consider in the multi-objective optimization of a building envelope.

The purpose of our article is to propose a method for optimizing the envelope of a building based on the energy load and taking into account daylight, which has not yet been investigated to our knowledge. Indeed, energy performance of buildings and daylighting studies are uncoupled and rarely studied simultaneously in the same software. Our goal is to propose a criterion for evaluating the annual daylight duration. Then, we establish a methodology to perform the optimization of the three objectives, namely the heating and cooling loads, and the daylight duration. For the optimization method, we chose the Pareto approach that finds the equally optimal solutions for the problem, i.e. the solutions that lead to the best compromise among antagonistic objectives. These results help with decision-making for building design. *A posteriori* preferences that depend on the specific problem may then be used to find a unique solution.[11] A case study based on the retrofitting of the façade of a dormitory is presented. In this application, the variables are the window type and the window-to-wall area ratio.

Optimization methodology

Case study

To illustrate our methodology, we applied it to an actual room in a dormitory selected for retrofitting. The building is made of identical rooms and has 5 levels. Computation was conducted for one room only. The room is located at an intermediary level, meaning one façade is external, the five other being adiabatic. Data used to compute the case is given in Table 1.

Table 1. Inputs for the case study.

Parameter	Value	Unit
Location	Pittsburgh, PA, USA	
Orientation	South–East	
Dimension of the room W × L × H	$4.27 \times 4.62 \times 2.59$	m^3
External opaque wall *U*-value	0.656	$W{\cdot}m^2{\cdot}K^{-1}$
Hygienic ventilation	1.5	ACH
Occupancy	2	People
Heating set temperature	20	°C
Cooling set temperature	26	°C

ACH: Air change per hour.

Variables

The variables of the problem are the ones that strongly impact the objective-functions, i.e. the types of the windows (discrete variables) and their areas (continuous variables), estimated as the window-to-wall area ratio WWR.

The discrete variables ''types of windows'' are characterized by their thermal and optical properties, through the transfer coefficient U-value and the visible and solar transmittances VT and ST, respectively. The visible transmittance characterizes the transmitted visible-spectrum flux. It impacts on the daylight through the value of the illuminance in the room. Associated to the visible transmittance, the solar transmittance, ST represents the transmitted solar flux, and plays a role in the solar gain that is beneficial during winter but detrimental during summer.

VT and ST were measured and given by manufacturers. As described in detail later, the illuminance was computed with the software Daysim. Note that Daysim requires the transmissivity, tn, of the window, which represents the transmitted solar flux but not taking into account the multiple reflections in each glass pane. The transmissivity, tn, was computed from the actual visible transmittance VT. The equation giving tn as a function of VT can be found in ref. [12]. Table 2 presents the 13 window types studied in the example; their associated characteristics of the triplets (VT, ST, U-value) were given by the manufacturers, and the calculated values of transmissivity, tn.

The window types are classified by increasing values of VT. These windows are existing windows found in the TESS library of TRNSYS.[13] They were chosen in

Table 2. Properties of the studied windows.

Window type	VT	ST	*U*-value ($W \cdot m^2 \cdot K^{-1}$)	tn
1	0.137	0.101	2.49	0.149
2	0.236	0.295	2.51	0.257
3	0.285	0.107	0.94	0.311
4	0.441	0.391	2.49	0.481
5	0.596	0.431	0.92	0.650
6	0.604	0.319	1.58	0.658
7	0.630	0.366	1.31	0.687
8	0.630	0.366	0.71	0.687
9	0.702	0.463	0.82	0.765
10	0.702	0.463	1.70	0.765
11	0.744	0.624	2.00	0.811
12	0.786	0.607	3.20	0.856
13	0.814	0.746	2.89	0.887

VT: visual transmittance; ST: solar transmittance; tn: transmissivity.

order to obtain a large panel of triplets (VT, ST, U-value).

Objective-functions

The objective of this article is to propose a methodology for simultaneously optimizing energy consumption and daylight. For this, three objective-functions have been developed: Qheat, Qcool, and ADDT.

We have chosen to characterize the energy consumption with the functions Qheat and Qcool, representing the heating and cooling energy loads, respectively. They were evaluated with TRNSYS 16.

Other indicators could have been chosen. It may be relevant to some applications to optimize summer comfort. Zhang et al.[3] and Sicurella et al.[14] proposed different indicators based on the indoor temperature that could also be used as objective-functions.

The choice of the objective-function dealing with daylight depends on the problem. In our case, the building under investigation was a dormitory that has to be retrofitted. In this application, the occupants were out of their room during the day. What is important is to increase the duration of daylight during a day, so that the occupants enjoy natural light in the morning and at the end of the afternoon. Therefore, the optimization criterion we chose was the duration when the illuminance was higher than a threshold, which was considered high enough not to require artificial lighting. The evaluation of this objective-function cannot be performed with TRNSYS. It was evaluated previously and is described in detail in the following section.

Description of the daylight objective-function ADDT

Computation of the illuminance E.

Daylight was quantified by the illuminance E, that is the luminous flux incident on a surface per unit area. The computation of the room was conducted with the Radiance and Daysim software packages.[12,15] Radiance is a backward raytracer that simulates indoor illuminance distributions due to daylight for one sky condition at a time.[12] Daysim is a daylighting analysis software that uses the Radiance algorithms to calculate annual indoor illuminance profiles based on a weather climate file.

Six façades with different WWR was modelled (Figure 1).

Illuminance was computed at the height of 0.85 m that corresponds to a standard desk's height, at the centre of the room. As mentioned previously, Daysim requires the transmissivity, tn, of the window. Therefore, the simulation to compute the illuminance was conducted for the 6 WWR; and the 11 different transmissivities, tn, are reported in Table 2.

Formulation of the objective-function ADDT.

It is worth noting that the time-step for the computation of the illuminance has to be small to obtain accurate results. Indeed, illuminance could be impacted by varying sky conditions much more than energy consumption would be. In this study, the time-step for the illuminance computation was 5 min whereas the time-step for the thermal simulation with TRNSYS was 1 h. The same weather data file was used for both the thermal and optical studies. The resulting file of illuminances was used to calculate the annual duration when the illuminance was higher than a threshold. In this example, we chose a value of 300 lux, which was high enough to conduct typical activities in a room.

Figure 2 shows the illuminance versus time for two specific days (June 21 and December 21) and two types of windows.

Types 1 and 13 have the lowest and highest visible transmittances, respectively. As expected, illuminance was higher when WWR and visible transmittance were high, and higher in summer than in winter. The instantaneous illuminance higher than 300 lux was integrated over time.

In the same way, the calculation of the time when illuminance is strictly higher than 0 lux is an indicator of day time. This time was invariable for all types of windows and WWR studied, and was equal to 4,176 h annually.

Figure 3 shows the annual time when $E > 300$ lux as a function of WWR, for the different types of windows studied. As expected, durations with sufficient daylight increased with windows transmissivities, tn and WWR.

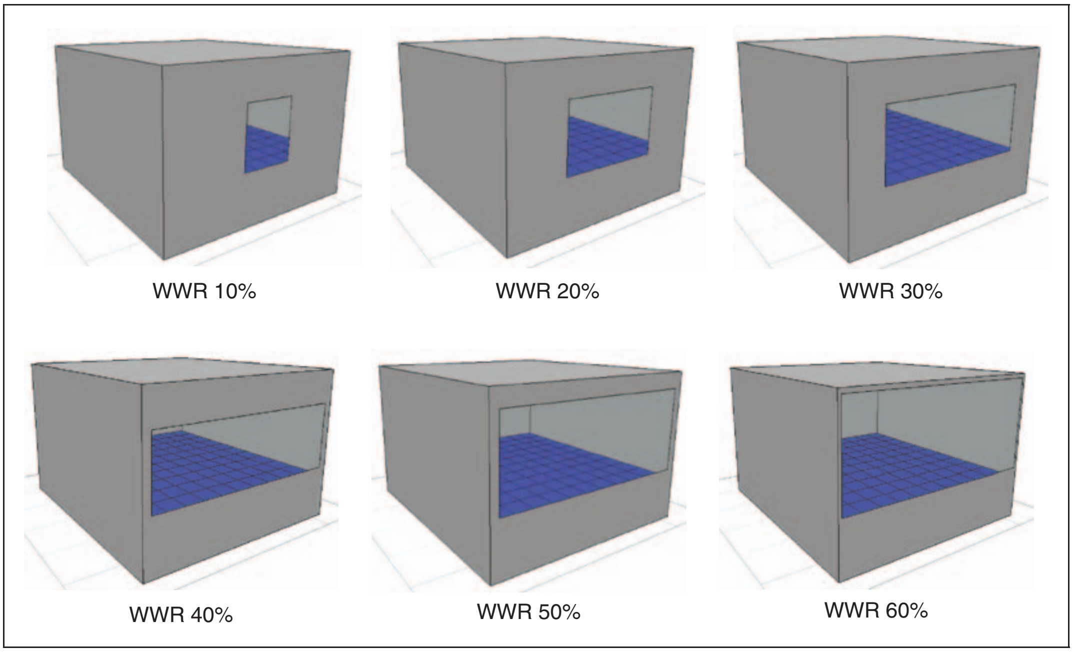

Figure 1. Window to wall area ratio (WWR) of the studied facades.

Correlations based on 5-order polynomial equations were found accurate enough to compute the duration when $E > 300$ lux as a function of WWR. These functions are named $ASDT_{300}$ for Annual Sufficient Daylight Time. The exponents of the polynomial equations, the values of the coefficients and the coefficients of correlation, r^2, were given in the annex for each window type.

The daylight objective-function aims to minimize the annual duration when the illuminance is lower than 300 lux, therefore deficient, and artificial lighting was required. This objective-function is called Annual Deficient Daylight Time (ADDT) and was calculated in hours. The function was written in conditional form as a function of the window type:

$$IF\ window\_identity = window\_type\ THEN\ ADDT = 4176 - ASDT_{300}$$

where data allowing the calculation of $ASDT_{300}$ for each window type is given in Table 3, and 4,176 represents the annual duration of daytime in hours, defined as duration when $E > 0$ lux.

Antagonistic effects of the variables on the objective-functions.

The variables (window type and WWR) can have a different impact on each objective-function. The higher the WWR, the higher the daylight, which could lead to minimize ADDT, as desired. At the same time, as windows have a higher transfer coefficient than the opaque wall, the higher WWR, the higher the heating load Qheat. Lastly, large WWR could lead to a higher solar heat gain and higher cooling load, Qcool. These variables have antagonistic effects on the objective-functions. An optimization method is therefore appropriate to solve this problem.

Optimization procedure

In the case where the number of potential solutions remains reasonably low, the determination of the set of solutions can be achieved. Conversely, if the number of variables and/or their range of variation are high, then stochastic optimization is more appropriate. In the particular case where the computation of the objective-functions is time-consuming (typically the annual energy load), one practical solution was to use an artificial neural network (ANN) to compute the objective-functions and then use multi-objective optimization to find the optimal solutions.[16]

In our case, we studied two variables: WWR and 13 discrete window types. Note that the objective-functions were nonlinear, monotonous functions that increase with WWR and not with the window type. Therefore, we achieved a sufficient accuracy by investigating a range of WWR from 10% to 60% with a 1% step. Finally, the number of potential solutions was 13×51.

The software GenOpt is a useful tool to perform parametric studies. GenOpt is an optimization program for the minimization of a cost function that is evaluated by an external program.[17] As its multi-objective optimization is only possible with derivative functions, it was not appropriated in our case. Yet, we used it to perform a parametric study to calculate the potential solutions. The algorithm spans a multi-dimensional

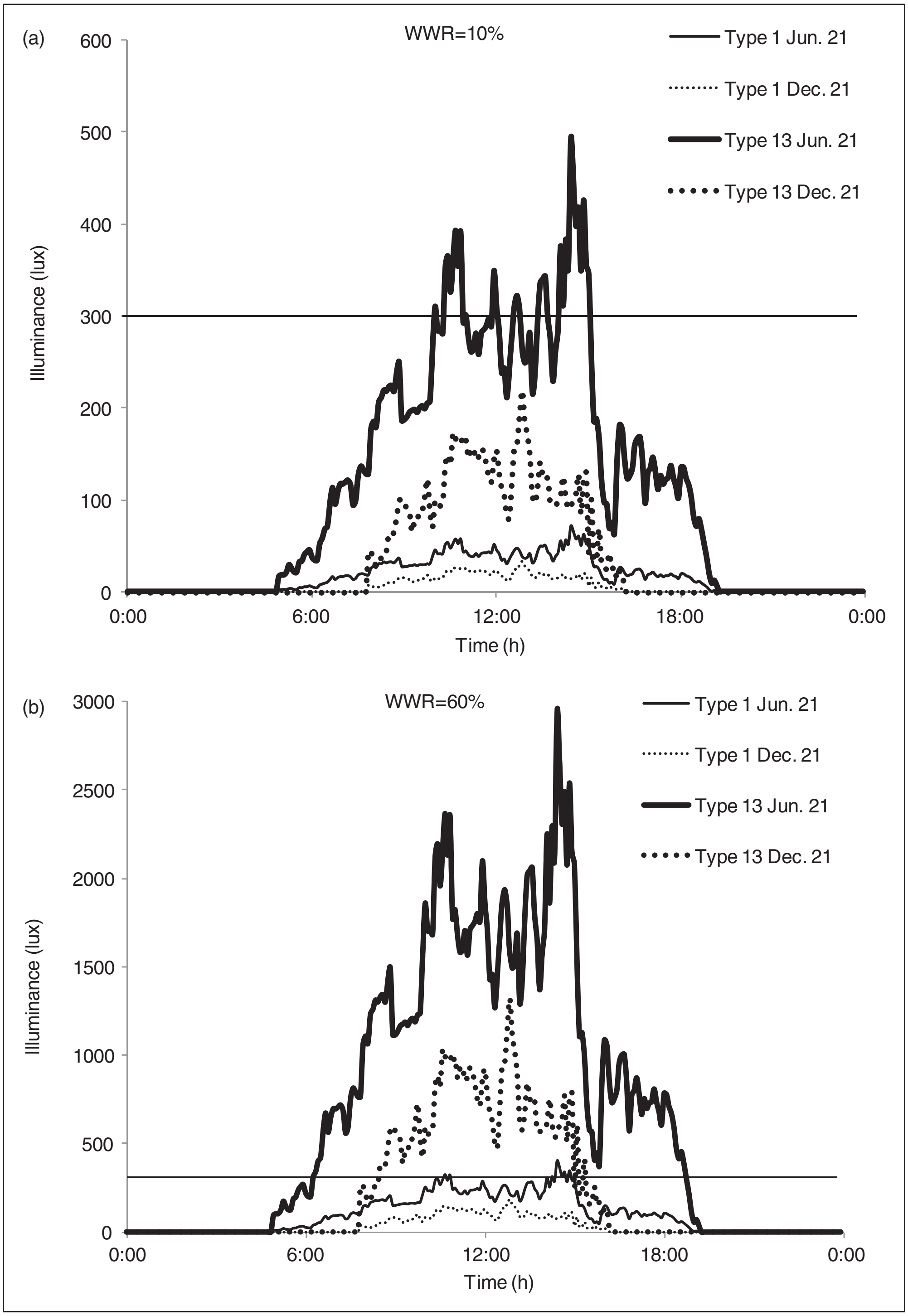

Figure 2. Daily illuminance for window types 1 and 13, for two window to wall area ratio (WWR) and two specific days.

grid in the space of the independent parameters, and it evaluates the objective-functions at each grid point. The variables and their range of variation were given as inputs in GenOpt, which is coupled to TRNSYS, which computed the objective-functions.

Once the set of solutions were obtained, the next step was to determine the optimal solutions among them. The multi-objective optimization method chosen was the Pareto approach. Pareto's simple idea of optimality in the case of multiple objectives can be verbally described as follows: "A solution is Pareto-optimal if it is dominated by no other feasible solutions, which means that there exists no other solution, that is superior at least in case of one objective function value, and

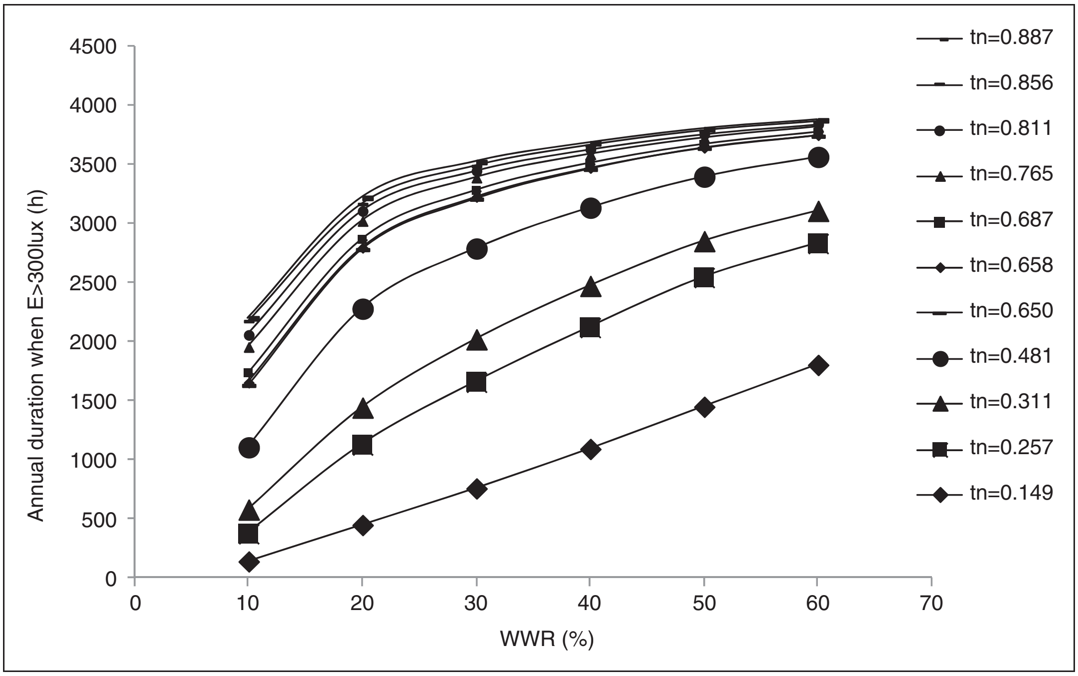

Figure 3. Annual duration when E > 300 lux ($ADST_{300}$) vs window to wall area ratio (WWR) as a function of the window transmissivity.

Table 3. Values of the objective-functions for some specific optimal solutions (the ones with a single value of WWR).

Window type	WWR (%)	Qheat (kWh)	Qcool (kWh)	ADDT (h)
3	10	1953	65.4	3599
5	10	1869	71.2	2555
7	10	1897	71.4	2452
12	56	4120	210.8	341

WWR: window to wall area ratio; Qheat: annual heating load; Qcool: annual cooling load; ADDT: annual deficient daylight time.

equal or superior with respect to the other objective functions values".[18] The non-dominated, optimal solutions formed a Pareto-front in the objective function space. The points that formed the Pareto-front did not dominate each other. None of them was better than the other, with respect to all of the objective-functions.[11]

Problems with multiple objectives are that they do not have a unique optimal solution but instead a set of Pareto-optimal solutions. The set of Pareto-optimal solutions are represented as a Pareto front, i.e. a hypersurface in the objective-function space.

Mathematically, the optimal solutions were computed as follows:

Let Fi(X), $i = 1, \ldots, n$, are objective functions for minimization.

A point X* is said to be Pareto optimal if there is no X such that Fi(X)< = Fi(X*) for all $i = 1, \ldots, n$, with at least one strict inequality.

Optimization results

Figure 4 shows all the potential solutions of the problem in the objective-function space.

They were grouped as lines, each one corresponding to a window type. Each point of the line corresponds to a WWR. This figure confirms that the variable WWR gives a monotonous characteristic to all the objective-functions. It validates the fact that a variation of 1% step in WWR was enough and that this variable did not need to be refined to an infinite number of values in the range, as has been reported in some articles. This figure also shows the solutions that are not optimal as having the highest values of the three objective-functions.

Figure 5 shows the Pareto-front made up of the optimal solutions among all the potential ones.

The Pareto-front is not continuous because of the discrete variables window types.[19] They are the optimal non-dominated solutions. Recall that all of these solutions have one objective-function out of the three that is lower than any other solution. They are equally optimal. This set of optimal solutions indicates that 2 window types among the 13 are never optimal; they are the types 2 and 4. Some of the solutions are optimal on all the range of WWR, such as types 6, 9, 10, and 11. Even if it cannot be seen clearly in Figure 5, the analysis

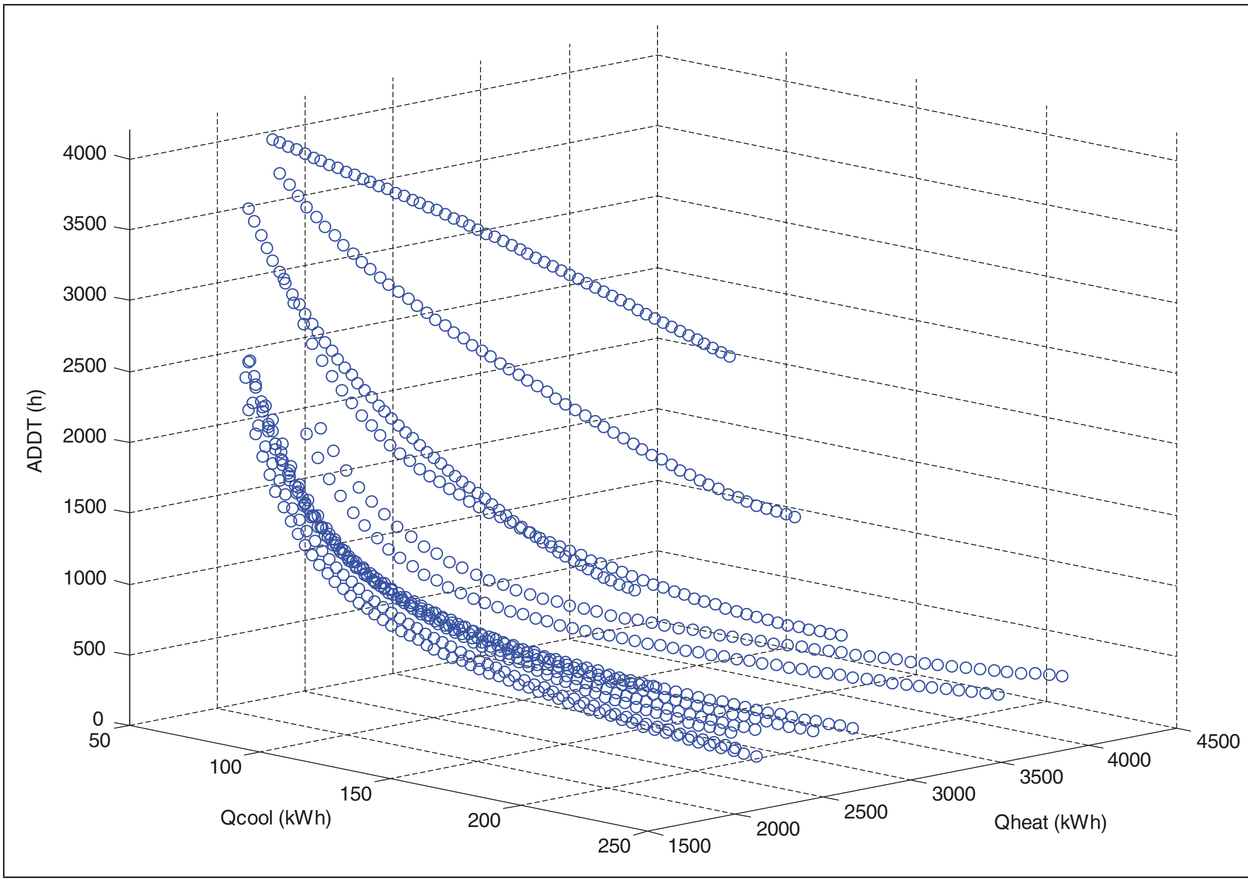

Figure 4. Potential solutions.

of the optimal solutions shows that types 8 and 13 are optimal for a large range of WWR but not on the entire range. Type 1 is optimal only for the three lowest values of WWR. Lastly, some windows types are optimal only for a single value of WWR, such as types 3, 5, and 7 that are optimal for WWR, which is equal to 10%. On the other hand, type 12 appears to be non-dominated only for WWR, which is equal to 56%.

A closer look at these last types, which are optimal only for one value of WWR, helps understand the definition of non-domination for 3 objective-functions. Table 3 gives the values of the 3 objective-functions for types 3, 5, 7, and 12. Each of these types has a value of one objective-function that is lower than the others. For example, types 3, 5, and 12 have the lowest values of Qcool, Qheat, and ADDT, respectively, among the four. Yet, type 7 is also optimal since it is non-dominated by the three others as it has always at least one value of an objective-function lower than the others.

Figures 6 and 7 show the objective-functions Qheat and Qcool as functions of the variable WWR for all the optimal solutions.

In order not to overload the figures, Figure 6 shows the solutions with several values of WWR per type, whereas Figure 7 shows the solutions with a single WWR per type. As expected, Figure 6(a) shows that when WWR increases Qheat increases because all the windows have a higher U-value than the wall. For a given WWR, types with low U-values lead to low Qheat. Figure 6(b) shows that Qcool also increases with WWR due to the higher solar heat gain. In this case, types with low U-value are not optimal for the cooling load since they prevent heat from going out and leading to overheating (e.g. types 8 and 9).

Figure 8 shows the evolution of ADDT as a function of WWR, for the optimal solutions.

The four specific optimal solutions with a single value of WWR are not reported (values are given in Table 3). For a given WWR, ADDT decreases as the visual transmittance VT increases.

The analysis of the window type is more difficult since it associates uncoupled variables (U-value, VT, ST) that have an impact on all the objective-functions.

Figure 6 shows that type 1 is appropriate for Qcool, for low WWR. Qheat and ADDT (shown in Figure 8)

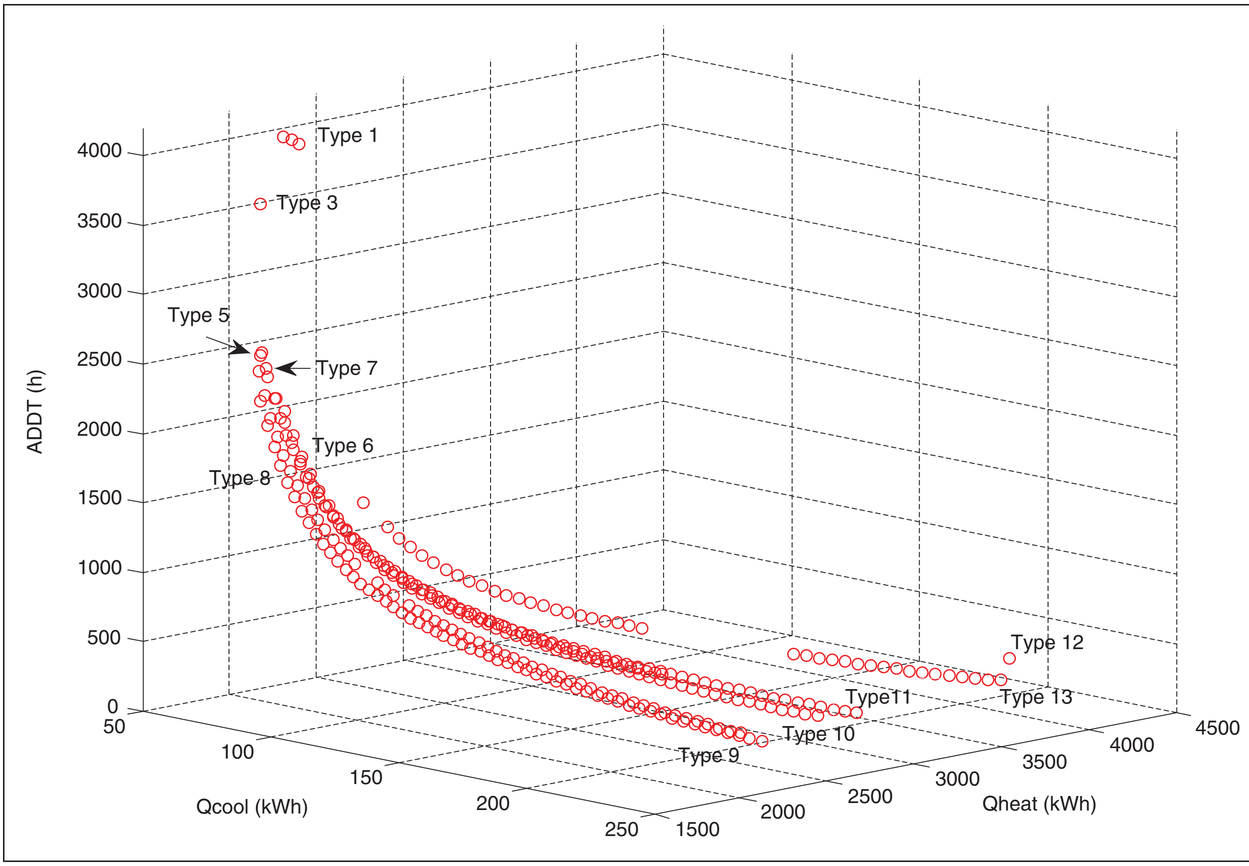

Figure 5. Pareto-optimal solutions.

are not optimal. Its low transmittance explains the good low value of Qcool and the bad value of ADDT.

Window types 9 and 10 have the same transmittance, leading to the same value of ADDT (Figure 8). They differ in their U-value, with type 9 having the smallest one. Logically, type 9 is suitable for the heating load (Figure 6(a)), whereas type 10 leads to lower values of Qcool (Figure 6(b)) because its higher U-value allows more heat to go out and limits overheating compared to type 9.

It is worth noting that the set of Pareto-optimal solutions can be further refined. From the decision-maker's point of view, the Pareto-optimal solutions have been evaluated without stating the relative importance of the individual objectives. Pareto-optimization provides the solutions for an optimal compromise, leaving the final selection to the decision maker. The decision maker may establish a preference decision *a posteriori*, by allocating a weight to an objective-function or setting some constraints by eliminating some solutions (e.g. the solutions with Qheat higher than 50 kWh.m^{-2}.year^{-1}), or by restraining the range of the variables. The value of this study is that we obtain the optimal solutions easily, which provides useful guidelines for decision-making.

Conclusion

This article proposes a method to simultaneously optimize three objective-functions, which are the heating load, the cooling load, and the annual indoor daylight duration. These functions being strongly non-linear and uncoupled, there is no other way to find the solutions of this problem than an optimization method.

The Pareto-optimization was chosen, as it is appropriate for optimizing several conflicting objectives. This method has been proven useful over a hundred years, enabling the determination of a set of equally optimal solutions that are helpful for decision makers. The variables of the problem are the window-to-wall area ratio WWR, and the window type, i.e. the optical and thermal properties through the triplet (VT, ST and U-value). The first step was to define the

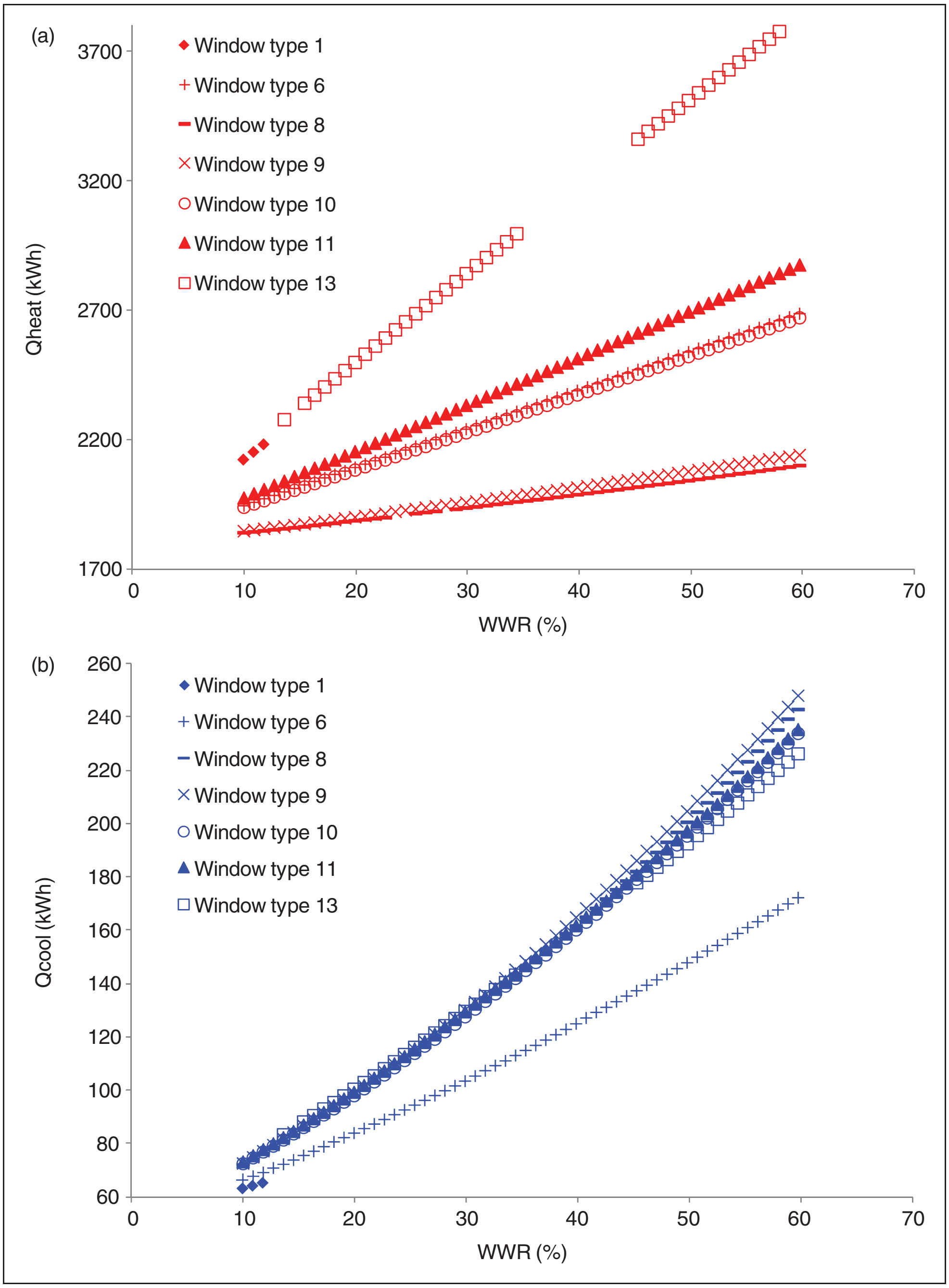

Figure 6. Objective-functions annual heating load (Qheat; a) and annual cooling load (Qcool; b) vs variable window to wall area ratio (WWR) for the optimal solutions.

objective-functions. In our case, the most complex was the one dealing with daylight. We calculated the annual duration when indoor illuminance was higher than a threshold, which was 300 lux in our example. This computation was conducted with the software Daysim by simulating cases and proposing correlation functions giving the annual indoor daylight duration as a function of WWR and the window type. Then, the set of the potential solutions was computed using GenOpt coupled with TRNSYS. Lastly, the optimal non-dominated solutions among them were calculated using the Pareto method.

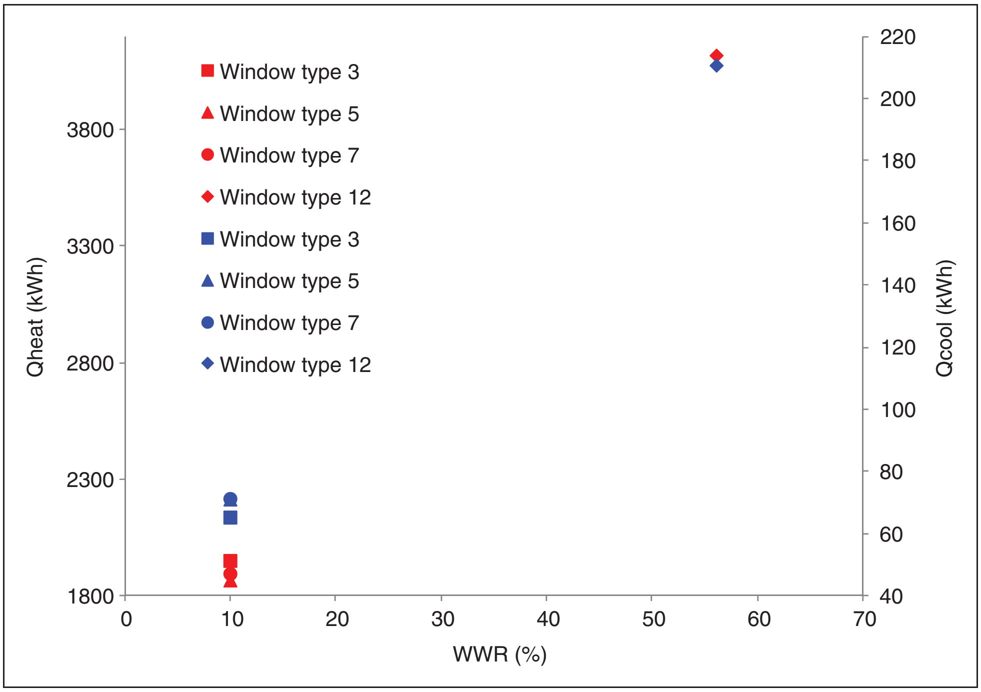

Figure 7. Objective-functions annual heating load (Qheat; in red) and annual cooling load (Qcool; in blue) vs variable window to wall area ratio (WWR) for some specific optimal solutions.

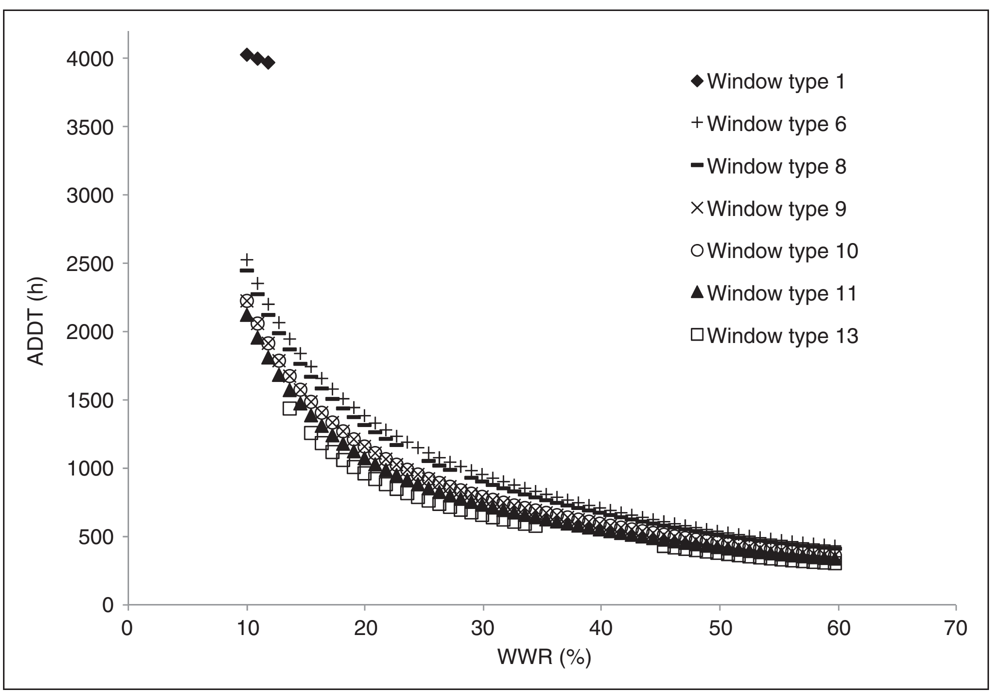

Figure 8. Objective-function annual deficient daylight time (ADDT) vs variable window to wall area ratio (WWR).

This method offers the advantage of quickly and accurately giving the optimal solutions of the problem, providing guidelines for construction decision. The method can be used for many other optimization problems. The same study can also be performed with fictitious windows by calculating the optimal VT, ST, and U-value in any range.

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